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The competent demand pull hypothesis: which sectors do play a role?

L'ipotesi della domanda competente: quali settori giocano un ruolo?

Cristiano Antonelli^{a,b}

Agnieszka Gehringer^c

^a Dipartimento di Economia, Università di Torino
Lungo Dora Siena 100A, 10153 Turin, Italy
E-mail: cristiano.antonelli@unito.it

^b BRICK (Bureau of Research on Innovation, Complexity and Knowledge)
Collegio Carlo Alberto
Via Real Collegio 30, 10024 Moncalieri (Turin), Italy

^c corresponding author:
Georg-August Universität Göttingen, Lehrstuhl für Wirtschaftspolitik
Platz der Goettinger Sieben 3, 37073 Goettingen, Germany
Tel. (+49)-5513933932, Fax: (+49)-551397093
E-mail: agnieszka.gehringer@wiwi.uni-goettingen.de

Sommario. Il lavoro propone e verifica l'ipotesi della domanda competente come fattore di traino del cambiamento tecnologico. L'ipotesi della domanda competente prende spunto dalla letteratura sulla 'demand pull' e argomenta che, piuttosto che la crescita della domanda aggregata, solo la crescita di una domanda qualificata in termini di competenza è effettivamente capace di trainare le capacità innovative dei fornitori solo quando e se questa proviene da soggetti con elevati livelli di competenza tecnologica ed è accompagnata da interazioni qualificate con i clienti. Il nostro contributo offre un test empirico dell'ipotesi, utilizzando i dati al livello del settore per diciannove settori (manifatturieri e di servizi), in quindici paesi dell'Unione Europea e rivolto al periodo 1995-2007. Nella nostra analisi facciamo uso delle tabelle input-output per misurare la forza delle interazioni settoriali relative alle transazioni dei beni intermedi. I risultati della verifica empirica confermano che la domanda, infatti, traina il cambiamento tecnologico solo se proviene dai clienti competenti che siano in grado di implementare effettivamente le interazioni ad alta intensità di conoscenza tra utilizzatori e produttori. I risultati, in particolare, mostrano la forte rilevanza delle transazioni-*con*-interazioni basate sulla conoscenza tra settori dei servizi ad elevata intensità di conoscenza e i settori manifatturieri.

Abstract. The paper investigates intersectoral linkages between manufacturing and services under the competent demand pull hypothesis. This hypothesis postulates that the demand pulls the innovative capacities of the suppliers only when and if they are accompanied by qualified knowledge interactions with creative customers. We empirically investigate this hypothesis based on the sector-level data of nineteen (manufacturing and service) sectors in fifteen EU countries over the period 1995-2007. We adopt the input-output framework to assess the strength of the inter-sectoral intermediate goods transactions. Our main findings confirm that demand actually pulls technological change only when it comes from competent customers able to implement effective user-producer knowledge interactions. The results stress the relevance of the transactions-*cum*-knowledge interactions between the knowledge intensive business service sectors and the manufacturing industries.

Keywords: micro-founded demand pull hypothesis; inter-sector relations; productivity growth

JEL O30

1. Introduction

In the recent literature on economics of technological change, there is a renewed attention on the role of demand in stirring and shaping the progress of technological landscapes (Nelson, 2013; Nelson and Consoli, 2010; Saviotti and Pyka, 2013a, 2013b). We refer to this literature as well as to the original post-keynesian model of demand pulled technological change (Kaldor, 1966; Schmookler, 1966) and reconsider the framework in a micro-founded context. The integration of the recent advances of the economics of knowledge, in fact, provides the opportunity to better focus on the role of the competent and specialized demand. In this way, it permits us to overcome the limits of the original interpretative framework elaborated by Nicholas Kaldor and Jacob Schmookler. The new approach, based upon a better understanding of the mechanisms of generation of technological knowledge in advanced economies, enables us to better identify which types of demand – generic or specific – are actually able to foster the introduction of innovations.

Moving on such a trajectory of conceptual underpinning, we empirically investigate, which sector-pairs are bilaterally involved in demand pulling mechanism generated by a competent downstream demand of intermediate goods. In this setting, a special attention is dedicated to the role of the transactions and related interactions between qualified manufacturing and intermediary service sectors in enhancing the efficiency-driven economic development of the entire industrial system. As a consequence of a downstream-upstream knowledge-based interaction that parallel and complement the vertical flows of transactions, total factor productivity (TFP) dynamics can be observed. Our dynamic panel data investigation permits us to overcome possible endogeneity problems and thus to obtain fully exogenous estimations of the underlying inter-sectoral relations.

The rest of the paper is structured as follows. Section 2 describes the standard formulation of the demand pull hypothesis and confronts it with its novel micro-foundations. This leads us to present in Section 3 the competent demand pull hypothesis. In this framework, we are able to discriminate the types of demand that, on the one hand, can stir the introduction of innovation and that are actually able to foster changes in total factor productivity and, on the other hand, the types of demand that produce negligible effects in terms of actual efficiency of the sector to which additional demand is directed. Section 4 describes the empirical methodology and the data. Section 5 presents the results of the

econometric analysis. The conclusions summarize the main results of the theoretical and empirical analysis.

2. Standard *versus* micro-founded demand pulling and productivity growth

The original demand-pull hypothesis, elaborated and articulated in the post-keynesian approach, contends that the increase of the final demand, by means of the multiplier and the accelerator, should lead to an increase of total investments. Through the positive capital accumulation, the aggregate output should raise (Kaldor, 1966). More precisely, investments should lead to increase the capital stock with new vintages of capital goods that are supposed to embody the most recent technological advances. As such, demand is expected to pull the introduction – or better the adoption – of new technologies. The generation of the necessary technological knowledge is supposed to take place automatically: no attention is given to the actual rates and directions of technological change. New technologies are on the shelf and the additional investments stirred by the increase in final demand enable to embody them in new capital goods.

In its original formulation offered by Nicholas Kaldor (1966), the demand pull hypothesis seems to apply more to the *diffusion* of innovations rather to their *introduction*. Indeed, the increase of final demand that leads to the increase of investments may foster the increase of total factor productivity through the *diffusion* of existing, most efficient, technological solutions. The Kaldorian demand pull hypothesis thus doesn't exclude that the technologies being diffused have already been developed and adopted. Consequently, this kind of demand pulling effects would stem from technical rather than technological efficiency increases. Most importantly, however, the Kaldorian demand pull hypothesis does not provide any specific clue to understanding why and how additional investment should foster the introduction of new technologies, rather than their adoption and diffusion. Moreover, it is clear that innovations and new technologies at large, in the Kaldorian demand pull hypothesis, are only process innovations embodied in new capital goods. No room is left to the possibility that demand pull implies the introduction of product innovations, not requiring new vintages of capital goods.

The demand pull hypothesis stems from the effort to provide an extension to the field of application of the Keynesian argument in favor of public demand. It was originally advocated and

applied only in periods characterized by recessive and even depressive conditions, to conditions of steady growth to foster its rates.

It seems clear that in recession, and even more clearly in depression, when there is a large excess capacity both in terms of unemployment and with respect to the installed productive capacity, an increase of demand will help increasing output and reducing the inefficiency levels engendered by low levels of excess capacity. Following Keynes, moreover, the public support to the aggregate demand might be able to push the system away from the liquidity trap and help it to find again the way to the full employment of productive capacities.

In order to contrast the implicit understanding that public demand was no longer necessary in periods of full employment, Nicholas Kaldor elaborated the hypothesis that even with full employment public demand could be effective: additional demand should stir additional investments that would embody new technologies with the final effect of increasing labor productivity, output and fiscal receipt.

Parallel to the scientific developments of the standard demand pull hypothesis, in a policy-anchored contest of the US innovation policy of the 1960s emerged the idea that innovation (to be sure military innovation) could actually be driven by demand, as engendered by publically financed R&D.¹

After the first period of intensive argumentations in favour of the demand-driven economic growth (according to Kaldor) and innovations (as in the circles of the US Department of Defense), more realistic approaches of the multidimensional kind emerged. The crucial contribution of these models was the recognition that demand is one of the crucial elements influencing innovative processes and other, supply-related factors assume concomitant importance.

In this spirit of the essential role assigned to economic – as opposed to purely technological – factors, the contribution of Jacob Schmookler (1966) qualifies and specifies the demand pull hypothesis. First of all, Schmookler recognizes both “knowledge” and “needs” as irremissible ingredients of economic progress. Second, he changes the focus from the final demand to the derived demand and, finally, provides a rationale to identify the sectors that are most likely to experience the

¹ See the excellent review paper by Godin and Lane (2013) for a complete discussion on the origins, development and death of demand pull hypothesis within innovation studies. The suggestion to recognize this related strand of the literature is the merit of an anonymous referee to whom we are very grateful.

positive effects of the demand pull dynamics. Schmookler focuses the analysis on the flows of technological knowledge – as proxied by the number of patents – actually generated in the system. He articulates the hypothesis that the demand engendered by the growth of specific activities – such as canals and railways – can push producers to activate new routines and dedicated research activities – that eventually lead to the actual introduction of new technologies. Such demand pulled *inventive* - as opposed to *innovative* - impulses might occur both intramural and extramural, often also with the direct participation of universities.

The empirical evidence elaborated by Schmookler shows that the flows of patents associated to specific technological fields can be explained – with proper lags – by the flows of investments in the corresponding industrial activities. The contribution of Schmookler is important because it does provide consistent micro-foundations to the macroeconomic level of analysis, originally suggested by Kaldor. Further efforts to better articulate the micro-foundations of the demand pull hypothesis enable to better focus and delimit its context of application.

The extension of application of the demand pull hypothesis from its original context, fully framed on the public and final demand side, into a demand pull hypothesis that highlights the private and intermediary components, changes radically its rationale and requires a major effort to provide new foundations. This notwithstanding, the demand pull hypothesis, even after the contribution of Schmookler, suffers from a clear limit: it does not provide a framework that is able to accommodate the obvious possibility and evidence that the increase of demand may have negative effects both in terms of efficiency and inflation.

According to standard economic textbook, an increase of the demand represented by the upward shift of the demand curve necessarily leads to an increase of prices. At the disaggregated level, moreover, in the short term, the increase of demand and the consequent increase of the prices push producers to move on the U shaped average cost curve to the right of the minimum towards input combinations that are more intensive in flexible inputs and clearly less efficient. An increase in demand – in the short term – necessarily yields an increase of prices and hence inflation and a reduction of total factor productivity and efficiency at large. In the long term – when and if – producers are able to change the more rigid production factors and move the map of isoquants in new

equilibrium conditions, the original conditions of efficiency will be restored. The supply curve can shift to the right. Costs and prices will return to the original levels. According to the standard textbook, in other words, the effects of an increase of demand cannot be anything else but a temporary decline of the efficiency of the activities, whose products are demanded, and a temporary increase of prices. The stretch of time along which the duration of the decline of the efficiency and the increase of prices is expected to last depends upon the rigidity of fixed production factors, or, in other words, upon the spell of historic time that is actually required to adjust the production process to the new desired levels of output.

The demand pull hypothesis holds only if the supply schedule actually shifts downward because of the upward shift of the demand schedule. This in turn implies that the demand pull hypothesis applies only if there is a clear causal relationship between the rates of increase of the demand and the introduction of innovations. Yet the traditional demand pull approach articulates the hypothesis that investments, stirred by additional demand, may eventually lead to the actual reduction of production costs via the increase of the general efficiency of the production process taking four strong assumptions for granted: i) investments automatically embody new technologies; ii) new technologies are necessarily embodied in new capital goods; iii) hence technological change is necessarily capital intensive; iv) new technologies are always and everywhere on the shelf, waiting to be used by the adopters.

Both the empirical evidence and the economics of innovation suggest that these assumptions could be too strong. First, it seems clear that the traditional demand pull hypothesis does not take into account the evidence about the resilience of old technologies: potential adopters may prefer to purchase capital goods embodying old technologies. The traditional demand pull hypothesis does not take into account the supply theories of diffusion according to which diffusion -i.e. adoption delays- is the result of the rational behavior of potential adopters that look forward to the introduction of incremental innovations and to the reduction of costs stemming from the introduction of process innovations. Second, new capital goods will bring technological advance only if they are actually technologically upgraded – a condition that cannot be given for granted. Third, technological knowledge is not necessarily embodied in capital goods with the consequence that technological

change is not necessarily capital intensive. New technologies are far from being capital intensive. The direction of technological change exhibits significant variance across time: new technologies seem characterized by high levels of skilled labor intensity. Finally, the evidence gathered by the economics of innovation shows that the rate and the direction of technological change are far from homogeneous and steady. The rates of technological change exhibit huge variations across firms, industries, regions and countries. In some extreme circumstances it does not take place in many periods of time and in many specific technological spaces: there are times and regions where no innovation is on the shelf waiting to be adopted.

The standard textbook analysis of the effects of the demand pull can be reversed only when and if the increase of demand actually pushes producers to timely introduce original innovations. The timely reaction is possible if new technological knowledge can be generated. In such a case, the reaction to the creative demand impulses is transformed in the generation of new technological knowledge, the introduction of new technologies and the eventual reduction in the marginal costs and no inflationary pressures should follow. The positive scenario is not obvious, automatic and cannot take place at all times and in all contexts. It can take place only when and if specific conditions qualify the market transactions with appropriate knowledge interactions. In this context, an economic theory of technological knowledge and innovations is necessary to integrate the notion of effective demand (Davidson, 2001).

The integration of recent advances of the economics of innovation and technological knowledge qualifies the conditions making possible that an increase of demand may actually engender an increase of the general efficiency of the production process. The downward shift of the supply schedule of the sectors that experience an increase in their demand can take place only as a direct and specific effect of the generation of new technological knowledge, the introduction of technological innovations. This in turn can take place only if pecuniary knowledge externalities are available (Antonelli and Gehringer, 2012). Pecuniary knowledge externalities are available when appropriate knowledge interactions between advanced users and receptive producers parallel the market transactions.

The effectiveness of such knowledge interactions is strongly dependent on technological and non-technological competences of both customers and suppliers. This brings us to recognize the role of

interactions between demand and supply side which became the focal conceptual ingredient of the multidimensional approaches initiated in the late 1970s and more recently formalized in the 1990s (see Godin and Lane (2013) for a critical review of the related models). According to Kline's (1985) "chain-linked model", the process of innovation is anchored into continuous interactions and feedback loops involving all the demand-side and supply-side elements. Recognizing this contemporaneous interplay occurring inside each industrial system, our emphasis goes further to stress on the kind of demand that is indispensable for such interactions to work.

3. The competent demand pull hypothesis

A competent demand pull hypothesis takes advantage of the recent advances of the economics of innovation and technological knowledge and this enables it to avoid the ambiguities of the standard demand pull hypothesis. More precisely, it can be built where the Schumpeterian legacy meets the Keynesian one and makes it possible to elaborate a much stronger because more concrete conceptual framework.

The starting point is found in the pathbreaking contribution of Schumpeter (1947) that introduces three crucial conditions for innovative outcome to be generated. First, unexpected events – such as an increase of demand beyond planned levels – cause out-of-equilibrium conditions: firms in different sectors try and react to the emerging out-of-equilibrium conditions. Second, their reaction can be merely *adaptive* or *creative*. The former consists in movements on the existing map of isoquants that lead to the standard textbook outcome previously described. The latter consists in the introduction of new technologies that change the map of isoquants and make possible to restore equilibrium conditions at higher levels of efficiency. Third, the creative reaction is possible only when and if producers can access external knowledge that, combined with internal knowledge, enables the generation of new technological knowledge and the introduction and adoption of superior technologies (Antonelli and Gehringer, 2013b). Both the introduction and the adoption of superior technologies require that new technological knowledge is generated: adoption is not the result of a passive conduct (Antonelli, 2008).

External knowledge plays a crucial role in the recombinant generation of the new technological knowledge. The actual generation of new knowledge, in fact, is possible only when and if all existing

technological knowledge can be accessed and used – both internal and external, both tacit and codified, both upstream- and downstream-sourced. External knowledge is strictly complementary – as opposed to supplementary like in the Griliches’s tradition of analysis (Griliches, 1979 and 1992) – to the internal knowledge inputs – ranging from competence to R&D activities (Weitzman, 1996 and 1998). Because of the strong and irreducible tacit content of technological knowledge, external knowledge can be effectively accessed and used, again, as a necessary and complementary input, only by means of qualified knowledge interactions with the original possessors and previous users (Antonelli, 2011 and 2013; Gehringer, 2011). User-producer interactions are one of the most effective vehicles of the market-based exchange of external knowledge (Von Hippel, 1993, 1994, 1998).

In this approach, the actual generation of new technological knowledge and the eventual introduction of new technologies cannot be regarded as a deterministic outcome. On the opposite, the likelihood that unexpected events actually lead to the final introduction of new technologies is a stochastic event that is highly sensitive to the specific and contextual conditions, in which the reaction of firms takes place. The creative reaction is possible only if, when and where a number of complementary conditions, including the actual availability of external knowledge and its access at costs that reflect the effects of pecuniary knowledge externalities, are actually possible.

This framework applies successfully to the competent demand pull hypothesis. Demand can actually pull the introduction and adoption of new superior technologies only if and when it is ‘competent’ i.e. originated by creative customers, able to support the upstream creative reaction with the provision of major pecuniary knowledge externalities. As a consequence, it has to be accompanied by qualified user-producer interactions that make the necessary access to external knowledge possible at costs being below equilibrium levels. In such conditions, external knowledge can be effectively used as an input into a recombinant generation of technological knowledge that can actually lead to the introduction of new technologies enabling the increases of total factor productivity. Technological change leads to the actual increase of total factor productivity only if, when and where firms can use external knowledge at costs that are below its reproduction levels (Antonelli, 2013).

Both the aforementioned conditions are necessary and alone not sufficient. When demand is not competent and takes place in a context whereby producers are not able to make their reaction creative,

its effects on upstream productivity are negative or negligible. Specifically, the effects of demand pull will be negative when the receivers of the additional flows of demand use rigid inputs which can be changed only in the long – historic – term. The effects will consist in the increase of prices and reduction of the efficiency of the production process that takes place in out-of-equilibrium conditions. The effects of demand pull will be negligible, in terms of total factor productivity, when producers cannot access external knowledge, but rely upon flexible inputs – both capital and labor – that make it possible to adjust quickly to the demand levels moving on the existing map of isoquants in equilibrium conditions. When instead customers are able to provide their suppliers with a consistent flow of external knowledge that can be accessed at low costs, hence, with low levels of screening, un-coding, absorption and learning activities, the reaction of suppliers to increasing demand can actually lead to the generation of new technological knowledge and the introduction of new technologies.

This framework leads us to focus attention on the types of knowledge interactions that link each sector to the others. Knowledge interactions are by definition bilateral: the active participation of both parties is necessary. Demand can pull the actual increase of efficiency by means of the introduction of superior technologies only if the *pulled* agents can actually generate new technological knowledge. This takes place if the *pulled* agents can activate fertile knowledge interactions with the *pullers* – the agents from which the increase of demand is originated. The identity of both the *pulled* and the *pullers* is relevant for the demand pull hypothesis to apply.

More precisely, consider A and B being two user sectors that demand the products of the producer sectors X and Y. We argue that the increase of the demand of A and B to X and Y will have positive effects on total factor productivity dynamics of X and Y only if the user-producer interactions between the downstream and the upstream sectors are competent enough to support the creative reaction of upstream sectors, resulting ultimately in the generation of new technological knowledge and the eventual introduction and adoption of new technologies. For the same token, we can elaborate further our argument. Assuming that both downstream sector A and B increase their demand for the products of the same upstream sector X, the effects will be stronger for the pair of sectors that has stronger user-producer knowledge interactions.

This approach enables to discriminate the effects of demand pull across sectors according to the conditions of the knowledge generation process. Demand pull does not apply everywhere and at all times: it applies only when the relations among users and producers enable to support the creative reaction of suppliers caught in out-of-equilibrium conditions by the unexpected increase of the demand. Pulled sectors will be able to actually innovate according to the quality of knowledge interactions with their pulling sectors.

The derived demand of downstream sector will be actually able to pull the increase of efficiency of the upstream sectors only if and when it is coupled with high levels of technological advance. The demand of the downstream sectors, in other word, can influence the innovation of upstream sectors only if it is expressed by knowledge intensive sectors. The increase of productivity levels in upstream sectors is actually pulled by the twin strictly complementary effects of: a) the increase of the derived demand of downstream sectors, and b) the increase of the levels of total factor productivity of the downstream sectors (Antonelli and Gehringer, 2012 and 2013a). The relationship between the two conditions is strictly multiplicative: when the increase of the derived demand is positive but the provision of external knowledge is zero the result is zero. This twin effect qualifies derived demand to become competent.

This argument leads to consider the competent demand pull hypothesis as a reliable clue of the quality and intensity of knowledge interactions at work between the users and producers. Because the increase in the demand of downstream sectors to upstream producers is not deemed to engender always positive effects, strong positive effects will be found only where the reaction of upstream producers has been creative because the user-producer knowledge interactions were strong(er). Negligible positive effects, both in terms of significance and size of the parameter will suggest that user-producer interactions are not sufficient to support the generation of technological knowledge in the upstream sectors. Negative effects, especially when still observed as the time goes by, indicate both the lack of qualified knowledge user-producer interactions and the rigidity of the production process of upstream sectors. In these cases, the reaction of upstream producers has been just adaptive. Whereas the rigidity should be absorbed in the long-run, the lack of qualified knowledge interactions requires crucial managerial innovations at the level of industry. Precisely, the managerial improvement

should be able to discriminate competent from non-competent demand impulses and, finally, redirect productive capacities towards the achievement of innovative outcome.

This approach permits us to specify a specific competent demand-pull variable, where the sheer increase of the levels of input demanded by downstream sectors is weighted by their growth rates of total factor productivity. The specification of this variable as a multiplicative relationship between the actual levels of intermediate demand expressed by downstream sectors and their growth rates of total factor productivity is expected to enhance the chances to grasp the crucial role of a competent demand as distinct from raw demand. This specification of the competent demand pull enables to appreciate the role of the stock of competence and technological knowledge of the downstream sectors together with the amount of their demand to the upstream sectors.

4. Estimation framework

4.1 Empirical methodology

We aim to grasp the demand pulling influence that competent downstream sectors exercise on productivity growth of the upstream supplying sectors. To properly exploit such an inter-sectoral map of relations, we base our investigation on input-output framework. It constitutes a powerful source of information regarding, among others, market-based exchange of intermediate inputs (Crespi and Pianta, 2007). It, moreover, is suitable to disentangle the precise, bilateral direction of flows between the supplying and receiving sectors. In particular, along the columns, one can read, for each single sector j , the requirements of intermediate goods received from each other sector and from its own. In the sense of rows, each line reports, for each single sector i , the values of intermediate inputs that are being supplied to each other sector and to its own.

In our empirical investigation, we are interested in the horizontal relations. More precisely, we aim to grasp the impact on total factor productivity (TFP) of each supplying sector i coming from the fact of being involved in intermediate goods transactions with each of its customer sector j . On their own, the demanding sectors are often innovative, with the consequence that such innovative capacities will be incorporated and transferred to the suppliers through the intermediate goods transactions. Thus, we are not interested in the demand pulling influence coming from the pure intermediate market transactions. Nor are we focusing on the pure technological interaction. What we aim to grasp is the

competent demand pulling influence on the innovative supplier that is simultaneously based on both market transaction and technological interaction with his innovative customer. As a consequence, for each single upstream sector i , we estimate the following empirical model:

$$\Delta \ln \text{TFP}_{i,g,t} = \beta_1 + \beta_2' \mathbf{r}_{i,g,t} + \beta_3' \mathbf{r}_{i,g,t-1} + \beta_4' \mathbf{z}_{i,g,t} + \gamma_g + \delta_i + \mu_t + \varepsilon_{i,g,t} \quad (1)$$

where $\Delta \ln \text{TFP}_{i,g,t}$ is the dependent variable referring to the logarithmic growth rate of TFP of a supplying sector i , in country g , at time t . On the right hand side, β_1 is a constant, γ_g , δ_i , and μ_t are the country, sector and time specific effects, respectively, and $\varepsilon_{i,g,t}$ is the idiosyncratic error term.

Vectors $\mathbf{r}_{i,g,t}$ and $\mathbf{r}_{i,g,t-1}$ include the crucial explanatory variables, measuring the productivity-enhanced demand-side influence coming from each single customer sector j at time t and $t-1$, respectively. In particular, each of the 19 variables in vector $\mathbf{r}_{i,g,t}$ describes each pair ij , where j refers to a single manufacturing or service sector, going from “food” to “real estate”, and i is the supplying sector from the left hand side of the equation. Such a variable, $r_{ij,g,t}$, is constructed as a product between the corresponding Leontief coefficient, $b_{ij,g,t}$ – taken from the i -th row of the Leontief inverse matrix, as described below – and the growth rate of TFP of the demanding sector j .²

In particular, coefficient $b_{ij,g,t}$ from the Leontief inverse matrix expresses the relative demand – direct and indirect – of intermediate inputs that sector j demands from sector i in order to produce 1 unit of final demand. It measures, thus, the relative intensity of market-based intermediate goods transaction between the demanding sector j and the supplying sector i .

Finally, in vector $\mathbf{z}_{i,g,t}$ we include three control variables. First, we construct a variable measuring an average supply-side influence on the productivity growth of sector i deriving from all forward linkages that this sector maintains with its suppliers by means of intermediate inputs transactions.³ The inclusion of this variable is motivated by the necessity to account for both the demand- and supply-side effects in a unique framework. This hypothesis we have already discussed in the previous section. Moreover, it has been confirmed in the past empirical investigations, for instance, by Mowery and Rosenberg (1979) and more recently by Arthur (2007). Second, we account for the

² For a full list of sectors taken under analysis, see Appendix A.

³ We follow the same method to calculate the supply-side variable described and used in Antonelli and Gehring (2013a).

possible demand-side effect coming from the sector-level non-competent, aggregate (intermediate and final) demand. Finally, we control for sector-level unit wages, in order to single out that the TFP growth dynamics – computed under the assumption of factor’s remuneration at marginal productivity – would be influenced by sectoral wage bargaining processes.⁴ Both variables are expressed in logarithmic terms.

When estimating the model represented in equation (1), we have to be aware of the possible endogeneity issues. This is because our right hand side sector-specific variables especially in vector $\mathbf{r}_{i,g,t}$ might be well affected by a common event or be involved in a reverse causality with the dependent variable. Indeed, nothing excludes that creative outcomes of the demanding sectors be triggered by innovative goods generated upstream.⁵ This implies the need to account for the dynamics of our estimation framework. Our choice is to estimate the model by means of dynamic ordinary least squares (DOLS), known also as the leads and lags approach. This method was proposed by Stock and Watson (1993) and described in Wooldridge (2009). It consists in adding to the right-hand side of the equation the leads and lags of the first differenced endogenous explanatory variables. In that way, the error term in equation (1) is decomposed into a part responsible for endogeneity of the explanatory variables and an exogenous one. This permits us to control for possible simultaneity and to obtain estimation results that are unbiased.

An important precondition for the application of the DOLS procedure is that the series are non-stationary and are systematically related over time, meaning that they are cointegrated. In Table A.5 of Appendix C, we provide evidence that both requirements have been fulfilled. Having found

⁴ We recognize the need to account for the effects of the sector’s internal R&D efforts. In our previous investigations, however, this variable was never significant (Antonelli and Gehringer, 2012 and 2013a). This was also the case in the present analysis, except for one case, namely for *rubber and plastic products*. There is another important limitation related to R&D data. Since data on sectoral R&D expenditures covering our sample are very incomplete, we would lose several observations by including it. Thus, in our main estimation procedure, we report the results from specification without R&D variable. Moreover, as explained below, the application of the DOLS procedure makes sure that there is no omitted variables problem.

⁵ This effect refers to the supply-push hypothesis between the supplying sector i (on the left-hand side) and the receiving sector j (on the right-hand side). We do not exclude this dynamics from being actually effective, but we concentrate on the demand pulling dynamics and overcome the possible reversal causality by means of an appropriate econometric methodology.

cointegration, we can be sure that our estimation results are not driven by spurious relationships and that omitted variables (which are lumped together in the error term) do not systematically influence the long-run relationship between TFP and the right hand side variables.⁶

In practical terms, given that our concerns regard the variables included in vector $\mathbf{r}_{i,g,t}$, we extend the model in equation (1) by the first differenced lagged and first differenced forwarded variables of that vector. Equation (1) becomes thus

$$\Delta \ln \text{TFP}_{i,g,t} = \beta_1 + \beta_2' \mathbf{r}_{i,g,t} + \beta_3' \mathbf{r}_{i,g,t-1} + \sum_{p=-1}^{p=1} \beta_4' \Delta \mathbf{r}_{i,g,t-p} + \beta_5' \mathbf{z}_{i,g,t} + \gamma_g + \delta_i + \mu_t + \epsilon_{i,g,t} \quad (2)$$

where Δ in the fourth component on the right side of the equation indicates that the variables in vector \mathbf{r} are first differenced. Moreover, $\epsilon_{i,g,t}$ is the new error term that is supposed to be heteroskedasticity robust.

Our dependent variable, TFP growth rate, is calculated as a residual from a Cobb-Douglas production function under the assumption of constant returns to scale. We follow the methodology of Jorgenson and Griliches (1967) and Jorgenson *et al.* (1987), who derive the logarithmic growth rate of TFP from the following expression:

$$\Delta \ln \text{TFP}_{i,g,t} = \Delta \ln x_{i,g,t} - \bar{\alpha}_{i,g,t}^k \Delta \ln k_{i,g,t} - \bar{\alpha}_{i,g,t}^l \Delta \ln l_{i,g,t} - \bar{\alpha}_{i,g,t}^c \Delta \ln c_{i,g,t} \quad (3)$$

where $x_{i,g,t}$ is total output of sector i in country g at time t , $k_{i,g,t}$ is sector-level capital stock, $l_{i,g,t}$ is labour force expressed as total employment and $c_{i,g,t}$ refers to intermediate inputs used in the production of the sector. Moreover, $\bar{\alpha}_{i,g,t}^f$ denotes the two-period average share of factor f over the nominal output defined as follows:

$$\bar{\alpha}_{i,g,t}^f = \left(\alpha_{i,g,(t-1)}^f + \alpha_{i,g,t}^f \right) / 2 \quad (4)$$

where $f = (k, l, c)$, whereas

$$\alpha_{i,g,t}^l = l_{i,g,t} / x_{i,g,t} ; \quad \alpha_{i,g,t}^c = c_{i,g,t} / x_{i,g,t} \text{ and } \alpha_{i,g,t}^k = 1 - \alpha_{i,g,t}^l - \alpha_{i,g,t}^c . \quad (5)$$

⁶ Under cointegration the error term is stationary; it becomes $I(0)$. An $I(0)$ variable which oscillates around a constant mean is statistically not able to systematically influence the non-stationary dependent variable. Consequently, it can be concluded that omitted variables do not affect and bias our results. Omitted variables could refer to different factors, such as institutional variables (for instance, industrial policies applied in certain countries and in certain sectors) but also other variables (e.g. human capital, specific innovation inputs).

Our choice to measure technological change in terms of TFP growth is motivated by the fact that this variable – on the contrary to other types of indicators – should grasp in the most complete way the innovative output generated within a productive activity.⁷ More precisely, its great advantage over patent-based measures is its ability to account also for innovations that haven't been put under the formal rules of intellectual property rights protection. Indeed, since the process of patenting usually takes time, is often complicated, and most importantly, expensive, innovators are not always willing to protect their intellectual property by means of a patent (Griliches, 1979; Pakes and Griliches, 1980). Similarly, also R&D expenditures were sometimes used to approximate for innovative capacities. Whereas R&D activities might be considered as a good measure of innovative input, the high risk associated with transforming ideas into measurable innovative outcome remains high and diminishes the possibility to precisely account for the latter, on which instead we focus most. Moreover, R&D-based measures refer only to budgetary resources dedicated to potentially innovative outcome and, thus, disregard the contribution of other kinds of innovative inputs (Acs et al., 2002).

To obtain our main explanatory variables in vector $\mathbf{r}_{i,g,t}$, we calculate – for each year between 1995 and 2007 and for each country in our sample – Leontief inverse matrixes that are obtained from the following expression:

$$\mathbf{x}_{g,t} = (\mathbf{I} - \mathbf{A}_{g,t})^{-1} \mathbf{y}_{g,t} = \mathbf{L}_{g,t} \mathbf{y}_{g,t} \quad (6)$$

where $\mathbf{L}_{g,t}$ is the Leontief inverse matrix for country g and at time t , $\mathbf{x}_{g,t}$ is vector of sector-level total production, \mathbf{I} is an identity matrix, with ones on the main diagonal and zeros elsewhere, $\mathbf{y}_{g,t}$ is vector of sectoral final demand and $\mathbf{A}_{g,t}$ is matrix of technical coefficients. A single cell of that matrix gives direct requirements of intermediate input expressed by a sector towards another sector, relative to the total production of the requiring sector.

4.2 Data

⁷ Following the seminal contribution by Solow (1957), this alternative indicator has been often referred to in different fields of the applied work to measure innovative outcome.

Our sample contains sector-level data for nineteen manufacturing and service sectors in fifteen EU countries in the time period 1995-2007. Appendix A reports the full and detailed information regarding the sectoral and country coverage.

Information on input-output tables has been taken from the World Input-Output Database (WIOD).⁸ From the tables, we could obtain the inverse Leontief matrix, as well as statistical information necessary to obtain other controls, namely, the average supply-side effect and final demand. Data necessary to calculate the growth rate of TFP and sector-level unit wages come from OECD STAN database.

Appendix B provides the correlation matrix (Tab. A.3) and descriptive statistics (Tab. A.4) of our variables used in the estimation.

5. Results

Our starting point is a brief analysis of a more general framework, in which we estimate our econometric model by pooling all sectors together. This permits us to obtain a general picture of the relative importance of manufacturing versus service sectors in pulling TFP growth at the system level. The results of the estimations according to the DOLS technique and the corresponding standardized coefficients are reported in Table 1. Standardized coefficients have the advantage of being reciprocally more comparable than the non-standardized ones. They are independent of the magnitude of change in each of the explanatory variable. Indeed, they say of how much the dependent variable changes subject to one standard deviation variation in the explanatory variable.

Table 1. Results of the pooled estimations.

	DOLS	Stand. coeff.
food	0.002 (0.002)	0.015
text	0.021** (0.002)	0.078
wood	0.248*** (0.002)	0.146
pap	0.037** (0.010)	0.083
chem	0.001	0.010

⁸ Detailed information regarding the data source for our investigation is provided in Appendix B. It also contains the correlation matrix and descriptive statistics of the variables.

	(0.057)	
rub	0.103***	0.154
	(0.017)	
onm	0.133***	0.137
	(0.034)	
met	0.004	0.025
	(0.010)	
mach	0.026***	0.087
	(0.008)	
elec	0.009	0.056
	(0.009)	
treq	-0.001	-0.008
	(0.005)	
manu	0.054***	0.095
	(0.015)	
util	0.027	0.108
	(0.013)	
constr	-0.008***	-0.146
	(0.003)	
whole	-0.007**	-0.093
	(0.003)	
hot	0.004	0.018
	(0.008)	
trans	0.001	0.011
	(0.003)	
fin	0.005	0.030
	(0.006)	
real	-0.009***	-0.249
	(0.002)	
N. obs.	3608	
R.-sq. overall	0.409	

Note: Estimations were run according to DOLS method. Robust standard errors are in parenthesis. ***, **, * report significance level at 1%, 5% and 10%, respectively. Country, sector and time fixed effects are considered. The coefficients on the lags, leads and on other controls are not reported.

The results suggest a relatively stronger importance of manufacturing than service sectors in generating the demand pulling influence, with a particularly important role played by *rubber and plastic products* (standardized coefficient of 0.154), *wood and products of wood* (0.146), *other non metallic mineral products* (0.137), *machinery and equipment* (0.087) and *textiles and textile products* (0.078). For services, the significant impact is signed by negative estimated coefficients. This evidence clearly confirms the outcomes of a previous study by Antonelli and Gehringer (2012).⁹

After having shown the most general results from estimations on a pooled sample, we can now pass to a more detailed analysis of inter-sectoral relations between manufacturing and services.

⁹ We are thankful to the anonymous referee for the suggestion to complete the picture with the pooled estimation. It constitutes indeed an important preliminary check before proceeding to a more detailed sector-to-sector analysis. We limit the discussion of these results to a minimum and refer to a more extensive treatment of the issue in Antonelli and Gehringer (2012).

The full set of the original sector-by-sector estimation results are reported in Table A.6 in Appendix C. In the current discussion, instead, our interest lays in designing and interpreting a complete matrix of relevant inter-sectoral relations, based on the competent demand pulling influence. For that reason, we report the standardized coefficients limitedly for the demanding sectors that were able to significantly pull the upstream productivity change in the original estimation procedures.

Tables 2 and 3 summarize the results of our calculations, where along the columns we can read the outcomes relative to the estimation procedure of each of the nineteen supplying sectors.¹⁰ More precisely, in Table 2 we report the results for the simultaneous demand pulling effects (at time t). Instead, in Table 3 we account for the possible lag between the moment, in which the demanding sector transmits its creative impulses to the supplying sector and the actual upstream reaction, resulting from that user-producer interaction. To keep the interpretation of the results more meaningful, we will read the tables horizontally, by looking at downstream sectors being effective in transmitting competent demand impulses. Moreover, in both tables, we shadowed two areas corresponding to *within* manufacturing (upper left) and *within* services (lower right) relations. The other two non-shadowed areas report the “asymmetric” or “between” demand pulling influence exercised by services on manufacturing sectors (lower left) and by manufacturing on service sectors (upper right). In the interpretation of the results both shadowed and not-shadowed areas are of interest as only in that way one is able to grasp the systemic nature of inter-sectoral relations involving at the same time manufacturing and service sectors.

Generally, it can be observed that the direction of the bilateral demand-side influence is mixed, with cases reporting both positive and negative sign of the coefficients. This evidence regards both the simultaneous effects of Table 2 and the lagged effects of Table 3. Such contrasting signs of the influence are supportive of the competent demand pull hypothesis and are fully accommodated by the reflections offered in the theoretical part of section 2. At the same time, it is important to note that the

¹⁰ In the last row, we report the standardized coefficients relative to sectoral aggregate demand (AD).

general tendency observed at the system level of a stronger influence coming from manufacturing sectors can be confirmed in this more disaggregated framework.¹¹

The heterogeneity of the results suggests that the sheer effects of the demand are intertwined with the effects of the knowledge generating conditions. When the influence of the demand is negative, the amount of technological knowledge provided by customers is not sufficient to support the introduction of innovations. The negative outcome expresses the loss in internal cost efficiency of the producers forced to move along the increasing part of the U-shaped average cost curve. This is because, in the short run, producers willing to profitably face the increase in demand are constraint to replace their current input combinations with the one characterized by a more intensive application of flexible inputs. Such combinations are clearly less efficient, but give the necessary survival opportunity until a new, lower average cost curve is achieved in the long run. This seems to have been the case of *rubber and plastic products* and *transport equipment* among manufacturing and *wholesale and retail trade* as well as *transport and communication* among services.

On the contrary, when the influence is positive, this means that producers possess still unexploited capacities. These capacities permit them either to move along the decreasing part of the U-shaped average cost curve or such producers are indeed able to take advantage of effective user-producer knowledge interactions that support their efforts to timely introduce technological improvements. This corresponds to the more efficient production modes and a new, lower, average cost curve. Here again the examples of typical high-tech sectors specializing in the provision of capital and intermediary goods such as *chemical products* and *machinery*, and among services, of *real estate* and *financial intermediation* are the most evident. On the opposite, we see that typical low tech sectors as *construction* and *wholesale and retail services* exert systematically negative effects.

Let us concentrate now on the four areas within the two matrices. Comparing the intensity of the influences between shadowed and not-shadowed areas, it becomes clear that the relations between manufacturing and services are relatively more intensive and also economically more important than

¹¹ Crucially, however, the results differ in the magnitude. This derives from the fact that in the pooled regressions the estimated coefficients measure a simple averaged impact of each sectors competent demand on the system-level TFP growth, whereas in the sectoral estimations this impact accounts for more precise features of sector-to-sector interactions.

for the two kinds of within relations (within manufacturing and within services). This is particularly true for the simultaneous demand pulling influence coming from manufacturing sectors and directed towards services (with an average, contemporaneous, effect of an increase in TFP growth by around 17 points following the variation by one standard deviation in the competent demand coming from manufacturing sectors – Table 2, and an average, lagged, effect of an increase by 10 points – Table 3), as well as for the influence of services on manufacturing sectors (Tab. 3; corresponding to an average increase in TFP growth by around 13 points). These results are most important as they confirm that the integration of competence between the service and the manufacturing industries is the most effective driver to support the rates of generation of new technological knowledge and the introduction of new technologies. The generation of technological knowledge and the eventual introduction of productivity enhancing innovations rely more and more upon the central role of the provision of competent services, like knowledge intensive business services (Doloreaux and Shearmur, 2012).

The closer and the stronger are the transactions between knowledge business service sectors and manufacturing sectors and the stronger are the opportunities for knowledge interactions to take place with the positive consequences in terms of larger access to external knowledge and hence faster introduction of technological innovations. The poor performances of all intra-services effects further qualify this interpretation. The demand of service sectors to other service sectors exerts negative effects. This result confirms that the coupling of service and manufacturing industries is the most effective field of application of the competent demand pull hypothesis.

The role of manufacturing sectors, as drivers of the competent demand impulses both towards other manufacturing and service sectors, should be also clearly acknowledged. The strongly positive impact coming from the *textile* sector (with an average effect of an increase in TFP growth by 41 units due to one standard deviation variation in the competent demand) is better understood in the light of intensive structural changes undergone by the sector in the late 1990s. Such successful restructuring activities often took place within the industrial districts, with an important supportive role played by the presence of upstream innovative suppliers, capable to respond to the novel technological needs of the restructuring plants (Antonelli and Gehringer, 2012).

On the single sector basis, crucial seems to be the lagged impact generated by *financial intermediation*. This effect was perceived by three crucial manufacturing sectors, *wood and products of wood*, *other non metallic mineral products* and by *machinery and equipment*. Moreover, it was not only statistically significant, but also economically among the most intensive. This evidence goes in the direction of the past empirical investigations confirming the Schumpeterian hypothesis on the crucial role of financial development in sustaining general productivity growth (Diamond, 1984; Boyd and Prescott, 1986; Greenwood and Jovanovic, 1990; King and Levine 1993). Also the lagged interaction between two important manufacturing sectors, *chemicals and chemical products* (as customer) and *electrical and optical equipment* deserves attention. Both are high-tech sectors, equipped with competences to let the market based user-producer interactions produce positive outcome.

Table 1 Summary results collecting standardized coefficients of explanatory variables (at time t) significantly influencing the dependent variable.

	<i>Dependent variable $\Delta \ln TFP$ in a column sector:</i>																		
	food	text	wood	pap	chem	rub	onm	met	mach	elec	treq	manu	util	constr	whole	hot	trans	fin	real
food						-17.27								-9.580			-17.18		
text			26.89											55.78					
wood	1.117		0.325																10.89
pap																			
chem										5.282									
rub							-16.89						-32.44				17.90	187.9	
onm				7.993															
met	13.70																		
mach													-17.52						-17.91
elec																			
treq	-32.51																		
manu						-7.736								-11.71					
util			59.64				21.42												
constr			9.426					3.270											
whole							53.53						-6.306			-3.675			
hot				-9.680															
trans										-22.41								-3.477	
fin																			
real																			
AD			-0.601			-1.127									-0.526				

Note: Explanatory variables express the demand-pulling technologically-intensive influence that each of the customer sector from the first column exercises on the supplying sector from *food, beverages and tobacco* (column 2) to *real estate services* (column 20). Reported standardized coefficients correspond to the estimation results that were statistically significant at least at 5% level. AD refers to the sector-level aggregate (but non-competent) demand. All estimations were run according to the fixed effects dynamic OLS model, where country, sector and time dummies are considered.

Table 2 Summary results collecting standardized coefficients of explanatory variables (at time $t-1$) significantly influencing the dependent variable.

	Dependent variable $\Delta \ln TFP$ in a column sector:																		
	food	text	wood	pap	chem	rub	onm	met	mach	elec	treq	manu	util	constr	whole	hot	trans	fin	real
food _{t-1}				15.77															
text _{t-1}		-0.193																	
wood _{t-1}						-10.36													
pap _{t-1}													17.86						
chem _{t-1}										8.235									
rub _{t-1}										-11.45							-15.94		
onm _{t-1}																			
met _{t-1}																			
mach _{t-1}						11.16													
elec _{t-1}			23.24																
treq _{t-1}										-5.486			29.448						
manu _{t-1}							10.133												
util _{t-1}										-9.897	-122.1								
constr _{t-1}	-23.75		-9.155							-11.21									
whole _{t-1}						-29.22													
hot _{t-1}																0.173			-5.556
trans _{t-1}			-93.32														-0.122		
fin _{t-1}			86.12				31.98		26.37										
real _{t-1}				4.957					21.41	41.78									

Note: Explanatory variables express the demand-pulling technologically-intensive influence that each of the customer sector from the first column exercises on the supplying sector from *food, beverages and tobacco* (column 2) to *real estate services* (column 20). Reported standardized coefficients correspond to the estimation results that were statistically significant at least at 5% level. All estimations were run according to the fixed effects dynamic OLS model, where country, sector and time dummies are considered..

A final comment is due to the effects generated by the sector-level aggregate demand. As the last row of Table 1 confirms, the influence generated by the generic non-technological although sector-specific demand (intermediate and final) was negligible or at most negative. This reinforces once again the role played by the competent – rather than generic – demand that takes place between creative users and producers.

6. Conclusions

The merging of the post-keynesian approach with the recent advances of the economics of innovation and knowledge enables to qualify and re-engineer the standard demand pull hypothesis articulating the competent demand pull hypothesis. The standard demand pull hypothesis was put forward in the post-keynesian literature to provide a rationale for the systematic active role of the public demand, moving away from the limits of a tool justified only in times of recession. Following the Kaldorian approach, in fact, all increases of public demand, by means of the interactions between multiplier and accelerator, are deemed to increase the levels of output because the additional investments stirred by the additional demand embody new superior technologies. New technologies are on the shelf: new investments are sufficient to foster their introduction and adoption that will engender an increase of the general efficiency of the system. The additional output engendered by capital accumulation was expected to yield automatically an increase of fiscal receipts, large enough to compensate for the excess demand, funded by deficit spending. The active role of the public demand was expected to be able to engender a continual increase of efficiency of the system, without increasing the burden of an ever increasing stock of public debt.

The evidence of the last decades of the XX century has suggested that demand pull can easily lead to inflation and the actual decline of the general efficiency of an economic system: generic, aggregate excess demand can easily push the system to produce in suboptimal conditions. The conceptual decline of the demand pull hypothesis parallels this gloomy evidence.

Quite on the opposite, the Schumpeterian legacy on the conditions for innovation generation provides the basic tools to rescue and qualify the demand pull hypothesis elaborated by the post-keynesian literature. The new understanding of the mechanisms that underlay the generation, use and exploitation of technological knowledge, elaborated by the new economics of knowledge, provides

new insights upon the conditions and qualifications that are necessary for the effective working of the demand pull hypothesis. Building upon these elements, we have put forward a ‘competent demand pull’ hypothesis.

The new competent demand pull hypothesis highlights the combined role of the multiplicative mix of pecuniary knowledge externalities and derived demand rather than that of generic demand. It applies in the special circumstances that make possible to combine the stimulations exerted by an increase in the levels of the derived demand for capital goods and intermediary inputs with the availability of qualified knowledge interactions that make the generation and exploitation of new technological knowledge actually possible. When downstream customers are competent knowledge user-producer inter-sectoral interactions exert a crucial role in the upstream recombinant generation of new technology that combines internal inputs of tacit and codified knowledge with external ones. The co-evolution of demand and knowledge generation conditions lies at the heart of the competent demand pull hypothesis. The demand pulling works if and when the generation of new knowledge is made possible by competent customers who make in the first place the coupling of market transactions and knowledge interactions between users and producers possible.

The results of the empirical analysis display a complex picture of bilateral relations between the competent users and innovative producers. The results generally confirm that the direction of upstream reaction to the downstream impulses coming from the competent demand is not rarely negative. This is driven by the need to replace the combination of inputs with a more intensive use of more flexible but at the same time less efficient ones. When, nevertheless, producers react creatively and achieve a more efficient map of isoquants, the influence turns to be positive. Within the manufacturing sector this was particularly the case of some of the high-tech sectors, specifically *chemicals* and *machinery*. The evidence confirms that the reciprocal and bi-directional interactions between the service and the manufacturing sectors are clearly most effective in fuelling the knowledge generation process. The demand for qualified services/manufacturing suppliers exerts strong and positive effects on the introduction of productivity enhancing innovations in the manufacturing/service sectors.

The policy implications of the analytical framework elaborated in this paper, well supported by the results of the empirical evidence, are strong and clear. The Keynesian intervention on the demand

side can conditionally provide important positive effects only when it is able to take advantage of the Schumpeterian legacy. If public policy aimed at fostering the rate of technological change by means of public procurement and general fiscal incentives, finalized to increase demand, is not based upon the identification of the competent sectors able to provide pecuniary knowledge externalities to their suppliers, it risks failing.

The new competent demand pull hypothesis is grounded upon the new understanding of the economics of knowledge. The competent demand pull hypothesis implies that the selective targeting of the recipients of additional demand is absolutely necessary. Within this framework, crucial becomes the working of the mechanisms that make the generation of technological knowledge actually possible. The mechanisms are necessary to lead the system towards the introduction and adoption of new technologies. New technologies do not fall from heaven and neither are they available on the shelf. New technologies can be generated by producers caught in out-of-equilibrium conditions such as unexpected increases of their demand levels only when and if strong knowledge user-producer interactions are at work. The identification of the couples of user-producer knowledge interactions is a necessary condition for demand pull effects to become actually strong and positive. The correct matching between pullers and pulled is found, where demand transactions and knowledge interactions are complementary.

The *selective*, as opposed to *generic*, use of public procurement plays an important role in this context. The competent demand for advanced products, combined with the direction of public research agencies, becomes an effective tool to promote the generation, dissemination and use of technological knowledge. Public agencies participate directly in promoting, sponsoring and guiding the creation of organized networks that cooperate in the provision of new, advanced products. Ex-ante coordination is combined with ex-post evaluation of the results. The intentional use of public procurement must be coupled with the direct supply of knowledge via the public research system so as to become a dedicated tool able to organize sophisticated platforms of innovative suppliers. Within such platforms, internal transactions can be systematically implemented with repeated interactions implemented by means of long-term open contracts (Edquist, Zabala-Iturriagoiti, 2012).

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Appendix A

Countries included in the analysis are: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, the Netherlands, Portugal, Slovakia, Spain, Sweden and the UK.

Table A.1 Full names and acronyms of analysed manufacturing and service sectors.

sector	full name
<i>food</i>	Food, beverages and tobacco
<i>textiles</i>	Textiles and textile products; leather and footwear
<i>wood</i>	Wood and products of wood and cork; articles of straw and plaiting materials
<i>paper</i>	Pulp, paper, paper products, printing and publishing
<i>chemicals</i>	Chemical and fuel products
<i>rubber & plastic</i>	Rubber and plastic products
<i>other non metallic min</i>	Other non-metallic mineral products
<i>basic metals</i>	Basic metals and fabricated metal products
<i>machinery & equip</i>	Machinery and equipment <i>nec</i>
<i>electr equip</i>	Electrical and optical equipment
<i>transp equip</i>	Transport equipment
<i>manuf nec</i>	Manufacturing <i>nec</i> ; recycling
<i>electr, gas & water sup</i>	Electricity, gas and water supply
<i>contruction</i>	Construction work
<i>wholesale</i>	Wholesale and retail trade; repairs
<i>hotels & restaur</i>	Hotel and restaurant services
<i>transport & comm</i>	Transport, storage and communication
<i>finance</i>	Finance, insurance
<i>real estate</i>	Real estate, renting and business activities

Appendix B

Table A.2 summarizes information concerning the definition of variables and their statistical sources.

Table A.2 Description of variables and their data sources.

variable	description	Statistical source
$\Delta \ln TFP_{i,g,t}$	Sector-level logarithmic growth rate of total factor productivity, obtained from a growth accounting exercise	OECD STAN database
$\mathbf{r}_{i,g,t}$	Vector of the main explanatory variables; each variable refers to the single sector demand-pulling and technology-intensive influence, constructed as a product between the corresponding element of the inverse Leontief inverse matrix (read in the sense of rows) and the growth rate of TFP of the demanding sector;	World Input-Output Database (WIOD) for calculating the Leontief inverses; OECD STAN for TFP growth
$\mathbf{z}_{i,g,t}$	Vector of control variables:	
<i>aver supply</i>	Average supply side influence, calculated as an average over all the supplying sector of the product between the respective element of the Leontief inverse matrix (read in the sense of columns) and the growth rate of TFP of the supplying sector;	World Input-Output Database (WIOD) for calculating the Leontief inverses; OECD STAN for TFP growth
<i>wage</i>	Natural logarithm of sector-level unit wage;	OECD STAN database
<i>aggreg demand</i>	Natural logarithm of sector-level aggregate demand composed of intermediate demand, final consumption by households, by government, by abroad, as well as gross fixed capital formation;	WIOD

Table A.3 Correlation matrix.

	tfp	food	text	wood	pap	chem	rub	onm	met	mach	elec
tfp	1.000										
food	0.114	1.000									
text	0.087	0.007	1.000								
wood	0.140	0.005	0.002	1.000							
pap	0.103	-0.003	0.002	0.016	1.000						
chem	0.265	0.002	0.002	0.001	0.003	1.000					
rub	0.130	0.002	0.003	0.005	0.006	0.003	1.000				
onm	0.113	0.001	0.000	0.007	0.005	0.004	0.006	1.000			
met	0.137	-0.001	0.004	0.014	0.008	0.012	0.006	0.019	1.000		
mach	0.129	-0.001	0.004	0.006	0.004	0.001	0.012	0.002	0.095	1.000	
elec	0.176	0.001	0.002	0.005	0.011	0.005	0.008	0.006	0.052	0.021	1.000
treq	0.198	-0.001	0.008	0.004	0.003	0.001	0.021	0.006	0.111	0.046	0.020
manu	0.120	0.005	0.011	0.047	0.008	0.004	0.013	0.008	0.026	0.015	0.006
util	0.119	0.001	0.000	0.001	0.000	0.005	0.001	-0.002	-0.005	-0.004	0.000
constr	0.137	0.007	-0.003	0.011	0.000	0.003	0.001	0.087	0.015	-0.008	-0.002
whole	0.087	0.014	0.003	0.002	0.008	0.002	0.003	0.002	0.008	0.001	0.005
hot	0.103	0.077	-0.002	0.003	0.003	0.001	0.008	0.005	0.005	0.002	0.006
trans	0.105	0.003	0.004	0.003	0.005	0.005	0.003	0.005	0.008	0.002	0.004
fin	0.118	0.001	0.001	0.001	0.002	0.000	-0.002	0.000	0.000	0.000	-0.001
real	0.080	0.000	0.001	0.002	-0.005	-0.002	-0.004	0.004	-0.002	-0.003	-0.003
AD	-0.074	-0.002	-0.025	-0.002	-0.031	0.018	0.017	-0.010	0.053	0.058	0.058
wage	-0.073	-0.004	0.008	-0.016	0.006	0.017	0.026	0.005	0.027	0.029	0.023
av. sup.	0.509	0.155	0.064	0.022	0.042	0.369	0.042	0.048	0.189	0.087	0.195

Table A.3 *con't*

	treq	manu	util	constr	whole	hot	trans	fin	real	AD	wage	av. sup.
tfp												
food												
text												
wood												
pap												
chem												
rub												
onm												
met												
mach												
elec												
treq	1.000											
manu	0.005	1.000										
util	-0.004	0.002	1.000									
constr	-0.006	0.016	0.004	1.000								
whole	0.001	0.002	0.002	0.015	1.000							
hot	0.003	0.002	-0.001	0.016	0.099	1.000						
trans	0.005	0.005	0.007	0.010	0.042	0.016	1.000					
fin	-0.001	0.001	-0.005	0.007	-0.005	0.001	0.013	1.000				
real	-0.003	0.004	0.006	0.017	-0.009	0.009	0.028	0.009	1.000			
AD	0.071	-0.011	0.020	-0.087	-0.019	-0.088	0.079	0.032	0.192	1.000		
wage	0.025	-0.011	0.005	0.003	0.017	0.016	0.020	0.024	0.001	0.155	1.000	
av. sup.	0.344	0.050	0.088	0.424	0.254	0.161	0.199	0.163	0.415	0.040	0.034	1.000

Table A.4 Summary statistics.

Variable	Mean	Std. Dev.	Min	Max	N. obs.
<i>ΔTFP</i>	0.002	0.040	-0.405	0.369	4520
<i>food</i>	-0.001	0.223	-8.414	4.583	4875
<i>text</i>	-0.002	0.095	-1.886	2.389	4875
<i>wood</i>	0.000	0.021	-0.465	0.471	4875
<i>pap</i>	-0.001	0.060	-1.318	1.052	4875
<i>chem</i>	0.009	0.631	-11.539	26.920	4875
<i>rub</i>	0.003	0.052	-0.540	1.106	4875
<i>onm</i>	0.000	0.029	-0.774	0.883	4875
<i>met</i>	0.008	0.234	-4.158	8.481	4875
<i>mach</i>	0.006	0.109	-2.090	2.123	4875
<i>elec</i>	0.017	0.302	-4.075	8.098	4875
<i>treq</i>	0.022	0.531	-11.180	12.396	4875
<i>manu</i>	-0.002	0.058	-1.373	0.931	4875
<i>util</i>	0.003	0.142	-2.640	4.471	4875
<i>constr</i>	-0.040	0.626	-18.484	10.034	4875
<i>whole</i>	0.000	0.345	-6.691	7.345	4875
<i>hot</i>	-0.019	0.197	-5.128	3.117	4875
<i>trans</i>	0.016	0.279	-3.625	5.280	4875
<i>fin</i>	0.007	0.280	-5.919	5.492	4875
<i>real</i>	0.066	0.708	-7.657	15.322	4875
<i>aggreg demand</i>	9.790	1.503	5.569	13.871	4875
<i>wage</i>	9.955	0.912	6.754	12.960	4849
<i>aver supply</i>	0.000	0.072	-0.860	1.073	4550

Appendix C

Below we show the details of the unit root test, of cointegration test (Table A.5) and of the DOLS estimations (Table A.6).

Table A.5 Results of the unit root test and cointegration test.

Sector	Series											
	<i>food</i>		<i>text</i>		<i>wood</i>		<i>pap</i>		<i>chem</i>		<i>rub</i>	
	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value
food	I(1)	0.186	I(1)	0.605	I(1)	0.843	I(1)	0.840	I(0)	0.000	I(1)	0.970
text	I(0)	0.024	I(1)	0.504	I(1)	0.217	I(1)	0.178	I(1)	0.258	I(1)	0.758
wood	I(1)	0.261	I(1)	0.653	I(1)	0.855	I(1)	0.109	I(1)	0.114	I(1)	0.978
pap	I(1)	0.240	I(1)	0.138	I(1)	0.933	I(1)	0.813	I(1)	0.132	I(1)	0.900
chem	I(1)	0.260	I(0)	0.012	I(1)	0.861	I(1)	0.565	I(0)	0.000	I(1)	0.440
rub	I(1)	0.162	I(1)	0.104	I(1)	0.884	I(1)	0.485	I(1)	0.151	I(1)	0.985
onm	I(1)	0.229	I(1)	0.310	I(1)	0.857	I(1)	0.692	I(1)	0.230	I(1)	0.958
met	I(1)	0.331	I(1)	0.154	I(1)	0.840	I(1)	0.373	I(1)	0.138	I(1)	0.926
mach	I(1)	0.228	I(1)	0.699	I(1)	0.620	I(1)	0.548	I(1)	0.211	I(1)	0.981
elec	I(1)	0.244	I(1)	0.152	I(1)	0.786	I(1)	0.606	I(1)	0.188	I(1)	0.880
treq	I(1)	0.116	I(1)	0.135	I(1)	0.935	I(1)	0.375	I(1)	0.116	I(1)	0.920
manu	I(1)	0.138	I(1)	0.212	I(1)	0.672	I(1)	0.866	I(1)	0.218	I(1)	0.581
util	I(1)	0.234	I(1)	0.103	I(1)	0.734	I(1)	0.854	I(1)	0.245	I(1)	0.489
constr	I(1)	0.108	I(1)	0.078	I(1)	0.568	I(1)	0.860	I(1)	0.128	I(1)	0.944
whole	I(1)	0.155	I(1)	0.357	I(1)	0.794	I(1)	0.838	I(1)	0.214	I(1)	0.909
hot	I(1)	0.116	I(1)	0.180	I(1)	0.880	I(1)	0.759	I(1)	0.119	I(1)	0.940
trans	I(1)	0.118	I(1)	0.150	I(1)	0.824	I(1)	0.759	I(1)	0.124	I(1)	0.904
fin	I(0)	0.006	I(0)	0.006	I(1)	0.870	I(1)	0.562	I(1)	0.112	I(1)	0.854
real	I(1)	0.142	I(1)	0.097	I(1)	0.910	I(1)	0.791	I(1)	0.931	I(1)	0.873

Note: Null hypothesis of the unit-root test: Unit root (individual unit root process); number of lags: 2.

Table A.5 *cont.*

Sector	Series											
	<i>onm</i>		<i>met</i>		<i>mach</i>		<i>elec</i>		<i>treq</i>		<i>manu</i>	
	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value
food	I(1)	0.728	I(1)	0.864	I(1)	0.935	I(1)	0.157	I(1)	0.260	I(1)	0.852
text	I(1)	0.321	I(1)	0.297	I(1)	0.554	I(1)	0.100	I(1)	0.361	I(1)	0.708
wood	I(1)	0.860	I(1)	0.925	I(1)	0.583	I(1)	0.188	I(1)	0.406	I(1)	0.789
pap	I(1)	0.497	I(1)	0.876	I(1)	0.885	I(1)	0.133	I(1)	0.248	I(1)	0.805
chem	I(1)	0.872	I(1)	0.884	I(1)	0.948	I(1)	0.184	I(1)	0.348	I(1)	0.872
rub	I(1)	0.862	I(1)	0.817	I(1)	0.933	I(1)	0.201	I(1)	0.204	I(1)	0.740
onm	I(1)	0.912	I(1)	0.875	I(1)	0.943	I(1)	0.223	I(1)	0.557	I(1)	0.734
met	I(1)	0.857	I(1)	0.888	I(1)	0.960	I(1)	0.290	I(1)	0.179	I(1)	0.849
mach	I(1)	0.847	I(1)	0.895	I(1)	0.971	I(1)	0.375	I(1)	0.130	I(1)	0.685
elec	I(1)	0.783	I(1)	0.892	I(1)	0.964	I(1)	0.400	I(1)	0.411	I(1)	0.853
treq	I(1)	0.870	I(1)	0.909	I(1)	0.900	I(1)	0.143	I(1)	0.509	I(1)	0.953
manu	I(1)	0.834	I(1)	0.902	I(1)	0.917	I(1)	0.201	I(1)	0.445	I(1)	0.899
util	I(1)	0.820	I(1)	0.907	I(1)	0.962	I(1)	0.238	I(1)	0.218	I(1)	0.925
constr	I(1)	0.895	I(1)	0.830	I(1)	0.931	I(1)	0.236	I(1)	0.345	I(1)	0.872
whole	I(1)	0.805	I(1)	0.712	I(1)	0.956	I(1)	0.242	I(1)	0.543	I(1)	0.913
hot	I(1)	0.639	I(1)	0.817	I(1)	0.912	I(1)	0.145	I(1)	0.559	I(1)	0.911
trans	I(1)	0.911	I(1)	0.722	I(1)	0.898	I(1)	0.268	I(1)	0.477	I(1)	0.929
fin	I(1)	0.709	I(1)	0.370	I(1)	0.956	I(1)	0.147	I(1)	0.249	I(1)	0.871
real	I(1)	0.645	I(1)	0.944	I(1)	0.259	I(1)	0.424	I(1)	0.918	I(1)	0.804

Note: Null hypothesis of the unit-root test: Unit root (individual unit root process); number of lags: 2.

Table A.5 *cont.*

Sector	Series											
	<i>util</i>		<i>constr</i>		<i>whole</i>		<i>hot</i>		<i>trans</i>		<i>fin</i>	
	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value
food	I(1)	0.659	I(1)	0.131	I(1)	0.192	I(1)	0.182	I(1)	0.542	I(1)	0.115
text	I(1)	0.178	I(1)	0.076	I(1)	0.138	I(1)	0.293	I(1)	0.272	I(1)	0.366
wood	I(1)	0.581	I(1)	0.126	I(1)	0.210	I(1)	0.207	I(1)	0.621	I(1)	0.409
pap	I(1)	0.813	I(1)	0.186	I(1)	0.224	I(1)	0.278	I(1)	0.473	I(1)	0.153
chem	I(1)	0.716	I(1)	0.197	I(1)	0.554	I(1)	0.312	I(1)	0.473	I(1)	0.952
rub	I(1)	0.255	I(1)	0.161	I(1)	0.299	I(1)	0.239	I(1)	0.704	I(1)	0.161
onm	I(1)	0.802	I(1)	0.132	I(1)	0.291	I(1)	0.120	I(1)	0.747	I(1)	0.115
met	I(1)	0.653	I(1)	0.172	I(1)	0.103	I(1)	0.348	I(1)	0.283	I(1)	0.374
mach	I(1)	0.738	I(1)	0.276	I(1)	0.205	I(1)	0.201	I(1)	0.090	I(1)	0.133
elec	I(1)	0.569	I(1)	0.168	I(1)	0.326	I(1)	0.127	I(1)	0.511	I(1)	0.087
treq	I(1)	0.773	I(1)	0.290	I(1)	0.553	I(1)	0.233	I(1)	0.864	I(1)	0.238
manu	I(1)	0.506	I(1)	0.317	I(1)	0.292	I(1)	0.215	I(1)	0.456	I(1)	0.092
util	I(1)	0.810	I(1)	0.490	I(1)	0.774	I(1)	0.275	I(1)	0.674	I(1)	0.324
constr	I(1)	0.295	I(1)	0.209	I(1)	0.110	I(1)	0.344	I(1)	0.113	I(1)	0.194
whole	I(1)	0.815	I(1)	0.373	I(1)	0.643	I(1)	0.238	I(1)	0.798	I(1)	0.245
hot	I(1)	0.695	I(1)	0.376	I(1)	0.627	I(1)	0.279	I(1)	0.597	I(1)	0.248
trans	I(1)	0.812	I(1)	0.521	I(1)	0.599	I(1)	0.225	I(1)	0.857	I(1)	0.168
fin	I(1)	0.613	I(1)	0.512	I(1)	0.654	I(1)	0.165	I(1)	0.571	I(1)	0.293
real	I(1)	0.358	I(1)	0.602	I(1)	0.332	I(1)	0.679	I(1)	0.188	I(1)	0.430

Note: Null hypothesis of the unit-root test: Unit root (individual unit root process); number of lags: 2.

Table A.5 *cont.*

Sector	Series								Cointegration test	
	<i>real</i>		<i>aver supply</i>		<i>wage</i>		<i>aggreg demand</i>			
	integr. order	p-value	integr. order	p-value	integr. order	p-value	integr. order	p-value	t-value	p-value
food	I(1)	0.257	I(0)	0.017	I(1)	0.978	I(1)	1.000	6.718	0.000
text	I(1)	0.307	I(1)	0.319	I(1)	0.959	I(1)	0.752	8.843	0.000
wood	I(1)	0.591	I(1)	0.274	I(1)	0.998	I(1)	0.999	5.186	0.000
pap	I(1)	0.181	I(1)	0.841	I(1)	0.701	I(1)	0.999	6.229	0.000
chem	I(1)	0.148	I(1)	0.546	I(1)	0.771	I(1)	0.897	16.090	0.000
rub	I(1)	0.572	I(1)	0.990	I(1)	0.947	I(1)	0.999	7.034	0.000
onm	I(1)	0.653	I(1)	0.964	I(1)	0.865	I(1)	0.999	5.976	0.000
met	I(1)	0.467	I(1)	0.935	I(1)	0.999	I(1)	0.995	4.931	0.000
mach	I(1)	0.311	I(1)	0.958	I(1)	0.972	I(1)	0.999	6.675	0.000
elec	I(1)	0.335	I(1)	0.489	I(1)	0.849	I(1)	0.971	9.675	0.000
treq	I(1)	0.405	I(1)	0.485	I(1)	0.919	I(1)	0.937	9.675	0.000
manu	I(1)	0.476	I(1)	0.854	I(1)	0.103	I(1)	0.997	6.976	0.000
util	I(1)	0.684	I(1)	0.865	I(1)	0.903	I(1)	0.992	7.300	0.000
constr	I(1)	0.572	I(1)	0.710	I(1)	0.965	I(1)	0.986	7.523	0.000
whole	I(1)	0.688	I(1)	0.638	I(1)	0.972	I(1)	0.988	4.409	0.000
hot	I(1)	0.581	I(1)	0.851	I(1)	0.165	I(1)	0.999	4.824	0.000
trans	I(1)	0.438	I(1)	0.880	I(1)	0.157	I(1)	0.955	5.523	0.000
fin	I(1)	0.277	I(1)	0.269	I(1)	0.993	I(1)	0.999	7.695	0.000
real	I(1)	0.676	I(1)	0.451	I(1)	0.786	I(1)	0.999	4.322	0.000

Note: Null hypothesis of the Dickey-Fuller unit-root test: Unit root (individual unit root process); number of lags: 2. Null hypothesis of the Kao-Chang-Chen cointegration test: No cointegration. Trend assumption: No deterministic trend.

Table A.6 Sector-by-sector estimation results based on the fixed effects model.

<i>Dependent variable: $\Delta \ln TFP$ in sector:</i>						
	food	text	wood	pap	chem	rub
food	0.034 (0.02)	-0.214 (0.47)	0.301 (0.36)	-0.649 (0.71)	0.114 (3.11)	-2.379** (1.17)
text	-0.431 (0.86)	0.124 (0.18)	7.204*** (1.81)	5.684 (3.72)	-14.608 (11.78)	-1.379 (3.09)
wood	1.898*** (0.71)	11.789 (19.04)	0.553*** (0.13)	0.572 (2.19)	-9.311 (31.48)	5.046 (5.50)
pap	-0.559 (0.76)	-23.064 (12.52)	0.444 (1.21)	0.080 (0.08)	3.800 (3.12)	0.315 (1.33)
chem	0.101 (0.12)	-0.415 (3.21)	1.589 (1.79)	-0.041 (0.18)	-0.006 (0.09)	-0.084 (0.13)
rub	1.406 (6.75)	23.376 (18.11)	3.888 (10.15)	4.831 (3.88)	-1.791 (2.15)	0.139 (0.33)
onm	-20.366 (23.51)	-8.518 (61.47)	7.333 (11.13)	7.739** (3.64)	3.739 (10.27)	-10.763 (7.93)
met	2.161*** (0.81)	1.612 (5.11)	-0.073 (0.68)	-0.818 (0.88)	-0.786 (1.72)	0.689 (0.41)
mach	1.678 (4.93)	-13.515 (14.15)	-3.516 (5.69)	-1.828 (1.94)	5.226 (5.05)	0.491 (1.59)
elec	-0.04 (1.15)	-0.149 (5.05)	0.276 (1.47)	0.126 (0.13)	-0.312 (1.00)	0.686 (0.46)
treq	-4.145*** (1.26)	-0.811 (2.29)	-1.543 (1.50)	-0.398 (1.07)	0.296 (2.27)	-0.127 (0.18)
manu	1.099 (2.77)	-3.71 (2.14)	-0.469 (0.36)	-2.852 (1.70)	5.84 (8.20)	-4.379*** (1.09)
util	2.356 (2.48)	52.67 (32.97)	14.97** (6.66)	-0.149 (1.65)	1.101 (2.25)	4.772 (3.04)
constr	-0.328 (0.55)	0.070 (3.70)	0.516** (0.24)	0.693 (0.68)	-1.16 (1.02)	-0.502 (0.30)
whole	-0.072 (0.18)	2.456 (2.28)	-2.409 (2.90)	-0.08 (0.24)	0.347 (1.32)	-0.454 (0.65)
hot	-0.029 (0.05)	-2.331 (3.79)	-3.968 (3.17)	-2.107** (0.92)	-1.39 (5.37)	0.171 (4.70)
trans	0.724 (0.83)	-3.961 (7.65)	-7.673 (4.06)	-0.102 (0.26)	1.233 (0.74)	-0.473 (0.92)
fin	-1.104 (0.71)	7.726 (24.28)	7.208 (6.77)	-0.351 (0.44)	-1.878 (2.73)	-4.000 (2.16)
real	0.475 (0.29)	0.089 (1.57)	0.84 (1.20)	-0.134 (0.14)	-0.118 (2.11)	0.615 (1.35)

Note: ***, ** and * report significance level at 1%, 5% and 10%, respectively. All specifications have been run according to the fixed effects model, with time dummy variables. We do not report results for the control variables, *average supply*, *wage* and *final demand* – they were always insignificant.

Table A.6 *cont.*

	<i>Dependent variable: $\ln TFP$ in sector:</i>					
	food	text	wood	pap	chem	rub
food _{t-1}	-0.007 (0.00)	-0.216 (1.10)	0.731 (0.64)	2.135* (1.07)	-1.607 (5.30)	-0.422 (2.98)
text _{t-1}	-1.086 (0.71)	-0.050** (0.02)	0.058 (2.47)	-2.954 (3.63)	4.547 (12.24)	0.409 (3.98)
wood _{t-1}	2.643 (1.50)	1.313 (11.31)	0.044 (0.06)	1.135 (2.31)	29.626 (32.57)	-17.56*** (5.34)
pap _{t-1}	-0.994 (2.32)	9.419 (13.62)	1.152 (0.74)	0.019 (0.01)	-0.583 (3.00)	1.189 (0.90)
chem _{t-1}	0.001 (0.41)	-0.268 (4.55)	0.09 (1.44)	0.126 (0.32)	-0.007 (0.01)	-0.098 (0.12)
rub _{t-1}	-11.419 (6.39)	-12.398 (12.30)	12.486 (8.81)	-0.509 (2.43)	1.426 (1.63)	-0.018 (0.05)
onm _{t-1}	-1.538 (12.05)	-8.274 (49.44)	-8.294 (8.58)	-3.054 (5.43)	1.342 (9.70)	8.772 (13.10)
met _{t-1}	2.905 (2.46)	4.233 (7.87)	0.704 (1.66)	2.269 (1.32)	-0.374 (1.49)	1.047 (0.88)
mach _{t-1}	2.997 (5.72)	-4.753 (10.07)	-1.416 (5.28)	-1.988 (2.39)	-5.946 (5.04)	3.550*** (1.08)
elec _{t-1}	-0.058 (0.99)	4.731 (3.50)	3.674*** (1.29)	-0.083 (0.16)	0.344 (1.34)	0.215 (0.22)
treq _{t-1}	-1.601 (1.39)	-0.097 (1.80)	-0.499 (1.10)	0.111 (0.29)	1.766 (1.18)	-0.253 (0.35)
manu _{t-1}	-4.224 (3.79)	-2.692 (3.42)	0.312 (0.42)	0.801 (2.25)	-5.914 (5.35)	0.643 (2.29)
util _{t-1}	4.423 (2.91)	22.05 (21.10)	4.239 (10.25)	0.121 (2.80)	-0.27 (2.43)	1.99 (4.15)
constr _{t-1}	-1.297*** (0.42)	-0.005 (3.79)	-0.500** (0.24)	-0.249 (0.59)	1.404 (1.77)	0.213 (0.43)
whole _{t-1}	0.362 (0.21)	-1.343 (3.05)	0.432 (2.36)	0.271 (0.24)	-1.286 (1.25)	-2.309** (0.90)
hot _{t-1}	-0.011 (0.07)	0.666 (2.84)	-0.236 (1.76)	-0.946 (1.25)	3.398 (3.82)	2.606 (2.11)
trans _{t-1}	-0.047 (0.63)	-4.183 (8.03)	-9.160*** (3.12)	-0.589 (0.44)	-0.993 (1.26)	-1.62 (1.05)
fin _{t-1}	-1.014 (1.19)	8.338 (10.13)	15.45*** (5.40)	0.171 (0.17)	-1.200 (2.28)	2.629 (2.56)
real _{t-1}	-0.15 (0.41)	-1.378 (2.00)	-0.421 (0.76)	0.201** (0.10)	-0.071 (1.36)	0.376 (0.84)
aver supply	-0.156 (0.42)	-0.465 (4.68)	-3.916 (3.74)	0.339 (2.10)	0.574 (2.19)	1.314 (8.12)
wage	-0.001 (0.00)	0.003 (0.01)	-0.002 (0.01)	-0.003 (0.00)	0.001 (0.01)	0.004 (0.00)
aggreg demand	-0.015 (0.01)	-0.009 (0.01)	-0.016** (0.01)	-0.006 (0.00)	-0.001 (0.01)	-0.030*** (0.01)
N. obs.	145	145	145	145	145	145
R-sq. overall	0.713	0.772	0.860	0.790	0.816	0.869

Note: ***, ** and * report significance level at 1%, 5% and 10%, respectively. All specifications have been run according to the fixed effects model, with time dummy variables. We do not report results for the control variables, *average supply*, *wage* and *final demand* – they were always insignificant.

Table A.6 *cont.*

	<i>Dependent variable: $\Delta \ln TFP$ in sector:</i>					
	onm	met	mach	elec	Treq	manu
food	-1.650 (1.55)	-1.140 (1.47)	1.860 (1.09)	-4.655 (3.92)	-3.908 (5.27)	1.487 (1.64)
text	4.368 (6.59)	-0.852 (3.07)	6.605 (11.20)	6.849 (8.24)	18.53 (15.12)	3.098 (2.74)
wood	4.923 (4.91)	0.144 (6.24)	4.305 (20.56)	-14.993 (19.34)	40.14 (37.02)	2.144 (1.74)
pap	-1.235 (0.83)	0.624 (1.38)	0.628 (1.85)	1.784 (2.32)	1.978 (12.08)	-2.191 (2.22)
chem	0.029 (0.18)	0.173 (0.28)	-0.153 (0.20)	0.539** (0.25)	0.159 (0.70)	0.518 (0.35)
rub	-11.316** (5.64)	-6.146 (5.58)	-0.681 (4.05)	3.104 (2.99)	-0.100 (2.29)	3.023 (4.24)
onm	0.535 (0.41)	7.967 (7.21)	4.877 (11.59)	-2.523 (10.90)	-8.427 (25.45)	-11.88 (10.07)
met	-1.299 (0.93)	0.044 (0.24)	0.29 (0.35)	-0.265 (0.37)	1.156 (0.95)	0.091 (0.19)
mach	3.145 (2.72)	0.189 (0.52)	0.308 (0.36)	-1.33 (2.01)	-1.269 (1.66)	0.804 (1.22)
elec	0.447 (0.78)	0.179 (0.22)	0.300 (0.34)	-0.051 (0.17)	0.272 (0.35)	0.906 (0.79)
treq	0.154 (0.70)	0.126 (0.12)	0.245 (0.36)	0.254 (0.45)	0.369 (0.38)	-0.999 (0.66)
manu	-3.779 (2.10)	-0.373 (0.62)	-1.369 (0.86)	-4.97 (4.03)	-10.02 (9.42)	0.262 (0.27)
util	5.378* (2.54)	1.674 (1.66)	2.139 (1.99)	-0.523 (1.73)	3.532 (7.91)	-0.928 (12.44)
constr	0.019 (0.06)	0.179*** (0.07)	0.711 (0.49)	0.428 (0.28)	5.009 (4.62)	0.853 (0.54)
whole	4.049*** (1.19)	0.648 (0.43)	1.676 (1.22)	1.695 (1.16)	-0.020 (2.05)	3.658 (2.11)
hot	-4.323 (2.44)	-1.119 (3.54)	-0.542 (2.46)	3.317 (2.90)	-1.263 (10.5)	-7.906 (4.53)
trans	-2.589 (1.53)	-0.264 (1.39)	-2.101 (2.34)	-2.082** (1.03)	-3.791 (2.31)	-2.738 (3.40)
fin	1.572 (2.06)	0.421 (1.84)	0.671 (3.97)	-2.959 (3.18)	7.059 (15.61)	1.315 (4.20)
real	0.622 (0.58)	0.100 (0.55)	0.222 (0.98)	0.412 (0.54)	-0.972 (2.88)	0.224 (1.20)

Note: ***, ** and * report significance level at 1%, 5% and 10%, respectively. All specifications have been run according to the fixed effects model, with time dummy variables. We do not report results for the control variables, *average supply*, *wage* and *final demand* – they were always insignificant.

Table A.6 *cont.*

	<i>Dependent variable: $\ln TFP$ in sector:</i>					
	onm	met	mach	elec	treq	manu
food _{t-1}	2.044 (2.75)	1.398 (1.69)	-1.358 (2.13)	3.501 (2.56)	2.515 (5.46)	0.519 (2.13)
text _{t-1}	1.922 (7.76)	1.265 (3.68)	-6.312 (8.22)	1.666 (7.85)	-9.141 (15.99)	-0.719 (3.33)
wood _{t-1}	-1.829 (8.11)	-5.755 (4.97)	-10.89 (10.12)	-36.21 (30.30)	-49.08 (60.16)	0.973 (0.98)
pap _{t-1}	0.283 (0.99)	0.535 (0.79)	1.42 (2.58)	0.853 (2.66)	-3.237 (5.66)	-0.452 (1.74)
chem _{t-1}	-0.089 (0.21)	0.366 (0.22)	0.177 (0.20)	0.836** (0.32)	-0.919 (1.77)	0.251 (0.31)
rub _{t-1}	0.807 (5.39)	-2.985 (3.23)	-2.701 (4.00)	-7.627** (3.87)	7.773 (5.70)	-1.837 (3.10)
onm _{t-1}	-0.032 (0.06)	3.501 (9.08)	-0.015 (13.38)	23.874 (15.26)	-68.52 (71.45)	-22.91 (19.65)
met _{t-1}	0.532 (1.00)	-0.021 (0.02)	-0.163 (0.11)	-0.072 (0.29)	-0.54 (0.30)	0.457 (0.44)
mach _{t-1}	-1.354 (3.24)	0.016 (0.29)	0.015 (0.03)	2.974 (1.57)	4.92 (5.08)	-1.107 (1.48)
elec _{t-1}	1.226 (0.81)	0.124 (0.08)	0.016 (0.39)	-0.001 (0.01)	0.511 (0.90)	-0.053 (0.76)
treq _{t-1}	-0.561 (0.54)	-0.049 (0.05)	-0.118 (0.13)	-0.704** (0.29)	-0.031 (0.03)	-0.769 (0.67)
manu _{t-1}	5.667** (2.77)	0.949 (0.50)	2.597 (1.68)	5.900 (4.00)	2.418 (8.46)	-0.002 (0.05)
util _{t-1}	4.443 (2.89)	0.478 (1.26)	-2.099 (1.70)	-2.550** (1.13)	-31.461** (14.30)	4.392 (6.01)
constr _{t-1}	-0.043 (0.05)	-0.091 (0.14)	-0.607 (0.44)	-0.612*** (0.16)	0.452 (1.93)	-1.042 (1.14)
whole _{t-1}	-1.000 (0.88)	-0.156 (0.69)	-0.098 (1.07)	-0.448 (1.60)	-2.714 (1.98)	0.032 (1.70)
hot _{t-1}	0.01 (2.48)	-1.852 (2.08)	0.874 (3.98)	-0.764 (4.28)	-2.637 (9.10)	1.005 (3.64)
trans _{t-1}	0.23 (1.64)	0.587 (1.05)	1.23 (2.09)	-0.727 (1.37)	4.901 (5.95)	-2.587 (3.50)
fin _{t-1}	5.738*** (1.20)	0.816 (1.87)	4.731** (2.34)	2.75 (2.41)	-0.984 (5.69)	4.68 (4.75)
real _{t-1}	0.072 (0.50)	-0.034 (0.29)	0.868** (0.38)	1.694** (0.66)	-0.387 (2.38)	1.064 (1.23)
aver supply	-4.194 (9.92)	-0.822 (5.89)	-6.451 (9.21)	2.347 (4.34)	-7.143 (8.56)	-4.497 (6.77)
wage	-0.001 (0.00)	-0.008 (0.01)	-0.005 (0.00)	-0.009*** (0.00)	0.000 (0.01)	-0.006 (0.01)
aggreg demand	-0.011 (0.01)	-0.003 (0.01)	-0.006 (0.00)	-0.003 (0.00)	-0.009 (0.01)	-0.008 (0.01)
N. obs.	145	145	145	145	145	145
R-sq. overall	0.854	0.899	0.795	0.888	0.666	0.788

Note: ***, ** and * report significance level at 1%, 5% and 10%, respectively. All specifications have been run according to the fixed effects model, with time dummy variables. We do not report results for the control variables, *average supply*, *wage* and *final demand* – they were always insignificant.

Table A.6 *cont.*

	<i>Dependent variable: $\Delta \ln TFP$ in sector:</i>						
	util	constr	whole	hot	trans	fin	real
food	1.300 (1.60)	-1.320** (0.60)	0.642 (0.92)	0.155 (0.15)	-2.367** (1.13)	-8.249 (13.63)	0.361 (0.83)
text	-0.157 (7.81)	14.95** (6.47)	-4.203 (2.28)	1.814 (5.50)	-2.295 (5.16)	57.11 (33.76)	6.030 (5.85)
wood	-8.666 (5.05)	0.681 (1.32)	4.095 (12.70)	14.987 (14.53)	7.843 (9.11)	109.32 (70.20)	18.51*** (7.93)
pap	3.791 (2.88)	2.644 (1.95)	0.137 (0.99)	-1.552 (1.86)	1.12 (1.06)	-2.058 (4.49)	-0.629 (0.60)
chem	-0.100 (0.10)	0.308 (0.26)	-0.088 (0.26)	-0.035 (0.50)	0.147 (0.08)	-0.821 (1.43)	-0.293 (0.20)
rub	-21.74*** (6.48)	3.311 (2.53)	-7.633 (5.08)	-9.64 (45.16)	11.99*** (4.34)	125.89** (58.60)	7.591 (8.89)
onm	19.337 (10.57)	0.39 (1.54)	7.648 (8.15)	-8.609 (19.78)	-6.163 (8.67)	-47.692 (47.54)	9.734 (5.64)
met	1.621 (1.14)	0.053 (0.19)	-0.398 (0.81)	-5.4 (3.62)	-0.293 (0.85)	2.265 (5.19)	0.872 (0.63)
mach	-5.235*** (1.61)	-1.906 (1.43)	-0.522 (3.23)	1.012 (7.56)	-1.495 (3.26)	6.724 (22.27)	-5.353** (2.58)
elec	-1.002 (0.65)	0.017 (0.21)	-0.44 (0.56)	1.787 (1.72)	0.000 (0.38)	-0.219 (1.49)	-0.342 (0.19)
treq	3.962 (2.06)	0.834 (0.89)	0.179 (0.49)	-0.365 (2.37)	-0.176 (0.48)	-4.324 (4.76)	-0.64 (1.03)
manu	-11.93 (8.30)	-6.630*** (2.54)	7.716 (4.29)	-10.55 (20.36)	-2.243 (6.90)	11.85 (11.88)	-3.851 (5.15)
util	-0.09 (0.13)	1.479 (1.05)	0.676 (0.69)	2.170 (1.78)	-0.299 (0.29)	0.739 (3.01)	0.036 (0.43)
constr	0.432 (0.74)	0.060 (0.04)	-0.065 (0.19)	0.412 (1.03)	-0.136 (0.15)	-0.688 (0.75)	-0.032 (0.05)
whole	-0.477*** (0.18)	0.331 (0.52)	0.015 (0.04)	-0.278** (0.13)	-0.121 (0.07)	-0.164 (0.50)	-0.109 (0.06)
hot	0.136 (0.64)	-1.252 (0.91)	-0.100 (0.16)	0.068 (0.09)	0.638 (0.55)	1.577 (2.00)	-0.537 (0.50)
trans	-0.196 (0.62)	-0.48 (0.48)	0.107 (0.07)	0.127 (0.51)	-0.014 (0.04)	-0.323** (0.16)	0.017 (0.08)
fin	0.877 (0.50)	0.164 (0.19)	-0.066 (0.18)	2.049 (1.47)	-0.032 (0.04)	-0.116 (0.11)	-0.014 (0.02)
real	0.246 (0.22)	0.162 (0.09)	-0.013 (0.17)	-0.738 (0.73)	-0.08 (0.07)	-0.183 (0.14)	0.007 (0.00)

Note: ***, ** and * report significance level at 1%, 5% and 10%, respectively. All specifications have been run according to the fixed effects model, with time dummy variables. We do not report results for the control variables, *average supply*, *wage* and *final demand* – they were always insignificant.

Table A.6 *cont.*

	<i>Dependent variable: $\ln TFP$ in sector:</i>						
	util	constr	whole	hot	trans	fin	real
food _{t-1}	-1.239 (1.28)	0.327 (1.29)	0.354 (0.59)	0.255 (0.16)	0.094 (1.01)	4.226 (13.61)	-1.462 (1.12)
text _{t-1}	13.18 (12.84)	1.121 (4.35)	-0.021 (2.50)	-8.643 (8.88)	-4.656 (9.67)	-67.17 (36.29)	3.190 (4.54)
wood _{t-1}	-2.497 (5.35)	0.370 (1.42)	17.404 (12.08)	6.984 (8.18)	4.978 (9.30)	26.383 (93.36)	9.820 (10.63)
pap _{t-1}	7.801*** (2.27)	-0.767 (1.21)	0.591 (0.85)	-2.499 (3.12)	0.019 (0.72)	0.917 (1.72)	-0.526 (0.69)
chem _{t-1}	0.015 (0.20)	0.329 (0.37)	-0.308 (0.31)	-0.827 (0.90)	0.086 (0.06)	0.027 (1.01)	-0.281 (0.22)
rub _{t-1}	-5.894 (9.94)	-5.575 (4.02)	-0.883 (4.09)	-25.65 (15.31)	-10.63*** (3.36)	-18.91 (62.56)	2.006 (7.53)
onm _{t-1}	18.787 (10.27)	-0.295 (0.99)	18.81 (16.16)	-26.873 (29.88)	13.813 (12.93)	20.11 (94.86)	-9.271 (8.83)
met _{t-1}	-1.828 (1.04)	-0.132 (0.26)	0.409 (1.53)	6.833 (4.71)	-0.05 (1.24)	14.87 (7.65)	1.290 (1.14)
mach _{t-1}	-0.979 (1.91)	2.075 (2.00)	0.253 (4.10)	7.094 (8.32)	-3.033 (2.87)	-0.308 (18.35)	-3.931 (3.00)
elec _{t-1}	-0.444 (0.43)	-0.116 (0.22)	-0.358 (0.55)	1.069 (1.03)	0.148 (0.29)	-0.28 (1.26)	-0.063 (0.32)
treq _{t-1}	3.779* (1.77)	-0.484 (0.60)	0.183 (0.43)	0.063 (1.62)	0.716 (0.41)	-0.136 (5.39)	0.309 (0.61)
manu _{t-1}	5.529 (12.82)	7.744 (5.83)	-4.647 (6.73)	-33.61 (21.26)	4.796 (8.83)	-51.52 (27.73)	4.219 (5.57)
util _{t-1}	-0.009 (0.02)	1.719 (1.40)	0.481 (0.57)	1.054 (1.61)	0.202 (0.52)	-0.796 (2.28)	1.321 (0.77)
constr _{t-1}	0.43 (0.77)	-0.016 (0.01)	-0.134 (0.44)	-0.882 (0.54)	0.142 (0.18)	0.694 (0.88)	0.022 (0.05)
whole _{t-1}	0.729 (0.50)	0.164 (0.39)	-0.002 (0.00)	-0.026 (0.07)	-0.073 (0.06)	-0.098 (0.48)	0.222 (0.12)
hot _{t-1}	-0.367 (0.61)	0.467 (1.04)	-0.046 (0.09)	0.039** (0.02)	-0.791 (0.52)	-0.490 (3.57)	-1.249*** (0.46)
trans _{t-1}	-0.591 (0.38)	-0.095 (0.19)	0.057 (0.11)	0.033 (0.71)	-0.012*** (0.01)	0.133 (0.32)	-0.103 (0.11)
fin _{t-1}	-0.49 (0.57)	-0.084 (0.16)	0.219 (0.13)	-2.968 (2.60)	-0.038 (0.04)	0.025 (0.02)	-0.061 (0.03)
real _{t-1}	0.218 (0.29)	0.032 (0.05)	0.107 (0.11)	0.677 (0.54)	0.053 (0.06)	-0.048 (0.08)	-0.002 (0.00)
aver supply	3.666 (2.95)	-0.787 (0.85)	-0.028 (0.93)	0.165 (2.16)	1.037 (1.04)	3.325 (2.96)	0.013 (0.10)
wage	-0.003 (0.00)	-0.010*** (0.00)	-0.001 (0.00)	-0.001 (0.01)	-0.004*** (0.00)	-0.010** (0.01)	-0.001 (0.00)
aggreg demand	0.019 (0.01)	0.001 (0.01)	-0.014** (0.01)	0.007 (0.01)	-0.002 (0.00)	0.006 (0.01)	-0.010*** (0.00)
N. obs.	145	145	145	145	145	145	145
R-sq. overall	0.855	0.806	0.826	0.576	0.877	0.639	0.831

Note: ***, ** and * report significance level at 1%, 5% and 10%, respectively. All specifications have been run according to the fixed effects model, with time dummy variables. We do not report results for the control variables, *average supply*, *wage* and *final demand* – they were always insignificant.

Cristiano Antonelli (1951) holds the chair of Political Economy of the University of Torino where he is President of the School of “Economics and Statistics”. He is Fellow of the Collegio Carlo Alberto where he guides the BRICK (Bureau of Research on Innovation, Complexity and Knowledge).

Agnieszka Gehringer (1982) has been a post-doc researcher in the chair for Economic Policy at the University of Göttingen, Germany, since September 2010. In July 2010 she completed her PhD studies at the University of Turin under the supervision of Prof. Cristiano Antonelli. Her research interests are lying in the field of innovation economics as well as in international economics.